13908

A Perception Test of Infrared Images of Soldiers in Camouflaged Uniforms

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ABSTRACT

Infrared (IR) images in the 3 to 5 and 8 to 12 micron band were taken of soldiers wearing various camouflaged uniforms. The soldiers wearing the uniforms were either standing, crouched or prone. The images were presented to 20 observers in the TARDEC Visual Perception Laboratory (VPL) and their detection decisions analyzed. Results were analyzed to determine which uniforms offered the most protection to a threat sensor. The laboratory results were modeled using the Fuzzy Logic Approach (FLA) with a resulting correlation of 0.9.

INTRODUCTION

The purpose of this experiment was twofold. The primary purpose was to determine which of 11 possible uniforms provided the most protection from detection with an IR imaging sensor to a soldier at night. The factors that were varied in the experiment were the range from the soldier to the sensor, the bandpass of IR sensor, soldier stance and the type of uniform. The image data taken in the field was converted and transformed for display on a computer monitor in a laboratory setting. The secondary reason to perform the experiment was to elucidate the concept of performing visual detection experiments in the laboratory setting as opposed to the field. Military field tests are very costly because of the security and equipment needed and field tests also have a problem with control of the important variables, such as ambient lighting. The premise behind a visual perception laboratory is that field test data and imagery can be supplemented in the controlled setting of the laboratory to permit a more careful control of the viewing conditions and permit an orderly collection of data from a large number of subjects.

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14. ABSTRACT
Infrared (IR) images in the 3 to 5 and 8 to 12 micron band were taken of soldiers wearing various camouflaged uniforms. The soldiers wearing the uniforms were either standing crouched or prone. The images were presented to 20 observers in the T ARDEC Visual Perception Laboratory (VPL) and their detection decisions analyzed. Results were analyzed to determine which uniforms offered the most protection to a threat sensor. The laboratory results were modeled using the Fuzzy Logic Approach (FLA) with a resulting correlation of 0.9.

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EXPERIMENTAL METHOD

Participants

A total of 37 active-duty military personnel of various assignments and experience levels participated. All the participants were male and were screened to verify they had 20-20 (or corrected to 20-20) vision. The participants volunteered for the study, and the study was conducted during normal duty shift hours. No other compensation was provided.

Stimuli and Apparatus.

The stimuli were black and white digital IR images of outdoor scenes. The target stimuli contained an image of a soldier in a background, while the distracter images presented the empty background. The combination of experimental factors dictated a total of 216 target-present stimuli. A single target-absent stimulus was created for each target-present factor level combination. The target-absent stimuli were duplicated to balance the proportion of target-present and target-absent images. The images were recorded on to VHS tape at night using two different infrared imaging cameras, shortwave and longwave. Examples of the stimuli images are shown below in Fig.'s 1 and 2. The imaging sensor specifications are as shown in Table I. The VHS tape was digitized using a Cosmo video capture board on a Silicon Graphics Indigo workstation. The images were digitized in RGB format at a resolution of 320 X 240 pixels. These images were then converted to a Windows 95-compatible format for presentation. At a nominal viewing distance of 25 in, the entire stimulus subtended a visual angle of 8.64 degrees in the horizontal, and 6.48 degrees in the vertical, while the instantaneous field of view was 0.03 degrees per pixel. The stimulus presentation and data collection routine was programmed in Visual Basic. The timing of image presentation and response data was accomplished with millisecond accuracy by calling the Windows 95 multimedia library. The Visual Basic program also contained the necessary routines for interactively controlling the pace and progression of the experiment, as well as providing initial instructions and data logging. The keyboard was used to log response information.

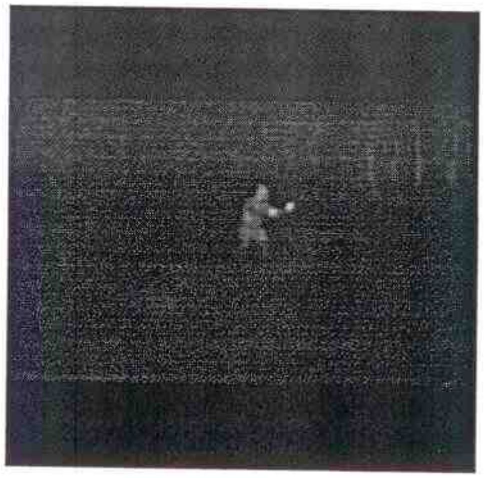


Fig. 1 Standing soldier

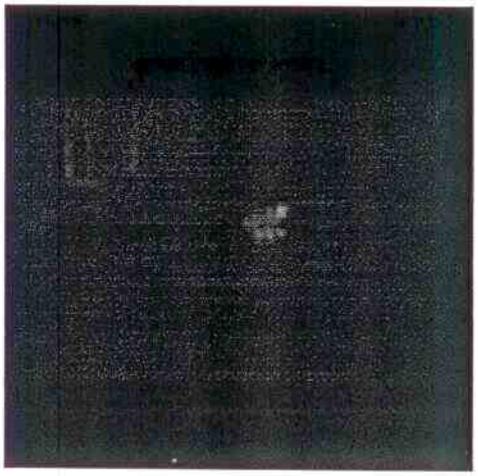


Fig. 2 Crouched soldier

TABLE I Field sensor properties

Parameter	Shortwave	Longwave
bandpass (μm)	2.75 to 4.50	8.0 to 12.0
IFOV (deg)	3.5 X 2.8	2.0 X 1.3
hor IFOV (mrad)	0.119	0.1135
ver IFOV (mrad)	0.1007	0.0675

Procedure

Observers participated in three sessions. Each session had an identical format. The sessions started with an initialization screen where the experimenter entered the participant's identification information. This was followed with a screen on instructions. A brief background on the task situation was provided and the participants were instructed that some scenes contained soldiers and others did not. Further, based on their perception of the scene, they were given three response options: (1) yes was reserved for cases where the participant was sure they saw a soldier in the field; (2) maybe was used to indicate that the participants saw something suspicious, but couldn't be sure it was a soldier; (3) no was reserved for cases where the participant was sure there was not a soldier in the scene.

After viewing instructions the participant hit the return key to continue, and started the first trial sequence. Each trial sequence proceeded in the following manner: First, an alert box popped up on the screen telling the participant to hit the space bar to continue. After hitting the space bar a mask screen appeared with a noise pattern. The noise pattern remained on the screen for an interval varying uniformly from 750ms to 2000ms to prevent anticipation effects in the pattern of responses. After the initial noise interval, the stimulus image appeared on the screen for 7 seconds. The participant was allowed to respond at any point after the stimulus image appeared. If the participant did not respond within 7 seconds, a second noise mask appeared in place of the stimulus image, with an additional prompt for the participant to respond. The Z, V, and M keys were labeled for use as the yes, maybe, and no response keys, respectively. This trial sequence proceeded throughout the randomly ordered trials dictated by the experimental design for all three sessions.

Design and Treatment of Data

Each of the three sessions served as a replicate in a full-factorial experimental design. Stimulus presentation order was randomized separately for each session. The independent variables were Sensor (short wave, long wave), Posture (prone, crouched, standing), Range (4 levels, ranging from target sizes of approximately 5 degrees to 10 minutes of arc), and Uniform (9 different uniforms). There was a no-target image for each target-present image in the experimental design. The resulting yes, no, and maybe responses were classified into hits, false alarms, misses, and correct rejections. This information was used to develop estimates of observer sensitivity (d) at two different response criterion levels, using the rating scale method shown in McMillan and Creelman (1996). The estimated true d was calculated as the mean of the liberal and conservative d values. ANOVA was performed on mean d value, calculated across all observers within each experimental cell.

ANALYSIS

The graph on the left side in Fig. 1 shows the value of the probability of saying yes given that a target is in the picture, P(Y) versus sensor and uniform. The P(Y) was computed on the basis of a YES response (Y) and the graph on the right side in Fig. 1 was prepared using the YES and UNCERTAIN (Y+?) response as the basis for the computation of the d-prime and probability of saying yes, or since the task was detection, probability of detection (Pd). The YES (Y) response gives a high criterion for a scene to contain a target. The (Y+?) response aggregation is a little more forgiving and basically provides a Receiver-Operator-Characteristic (ROC) curve that gives a medium criterion for selecting a scene as containing a target. Each plot also shows how P(Y) changed versus run number. There were 3 runs per subject and because of time constraints, the soldiers had to do the tests sequentially with no break, so their performance did degrade slightly. For both sensors, system 8 is the system that provides the best camouflage to the soldier in the backgrounds used in the field data collection. Sensor 2 was the short wave (3-5 micron) sensor and sensor 1 was the longwave (8-12 micron) system. Generally, the shortwave (SW) systems have a higher resolution, or have greater contrast, than the longwave (LW) systems. However, the LW systems generally perform better under adverse weather conditions and for long ranges because of the wider window between 8 and 12 microns and less energy loss due to atmospheric scattering. It therefore makes sense that the LW system performed better over range and other environmental variables which caused the various uniform systems to be more detectable through the LW IR sensor.

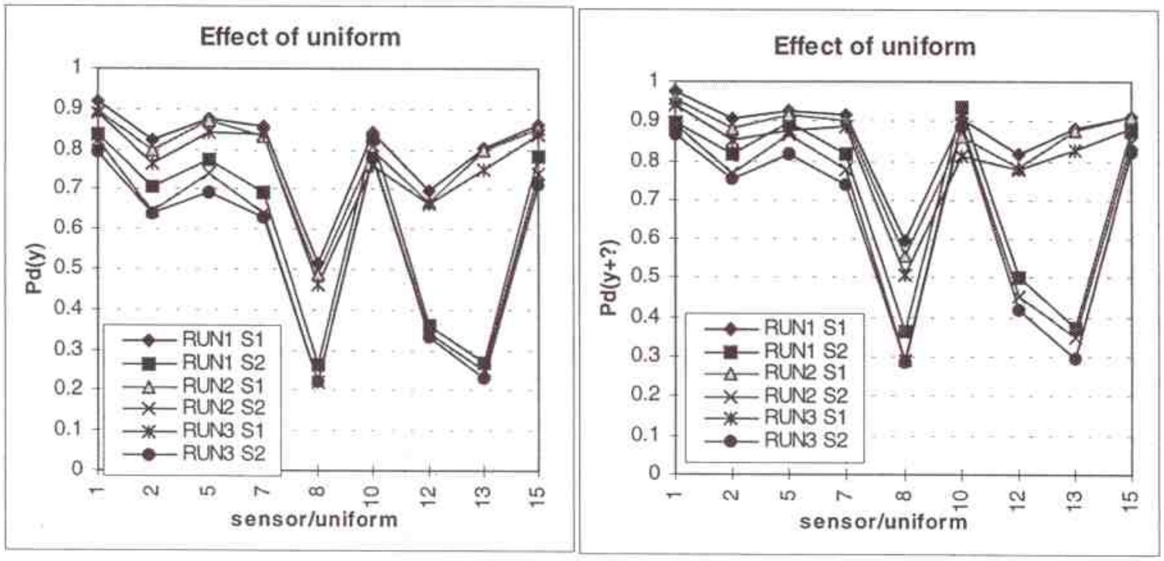


Fig. 1 Comparison of the Probability of detection by uniform and sensor

For each sensor, there is a monotonic decrease in dprime as a function of distance Fig. 2 shows how the detectability metric d-prime changed as a function of distance for both SW and LW systems. In this graph d-prime was aggregated over all factors and both response bias's are shown. The curves of the detectability decrease with distance. An exponential fit to the curve explains greater than 95% of the variance. The rate of descent of d-prime versus distance is a little steeper for sensor 2 than sensor 1, which makes sense because the performance of the SW system is known to decrease very fast with increasing range. SW systems are best used for very close-up, short-range surveillance. Sensor 2 was the short wave (3-5 micron) sensor and sensor 1 was the longwave (8-12 micron) system. Generally, the shortwave (SW) systems have a higher resolution, or have greater contrast, than the longwave (LW) systems. As shown above in slide 2, the LW system was the greater threat to detection of the all the uniforms.

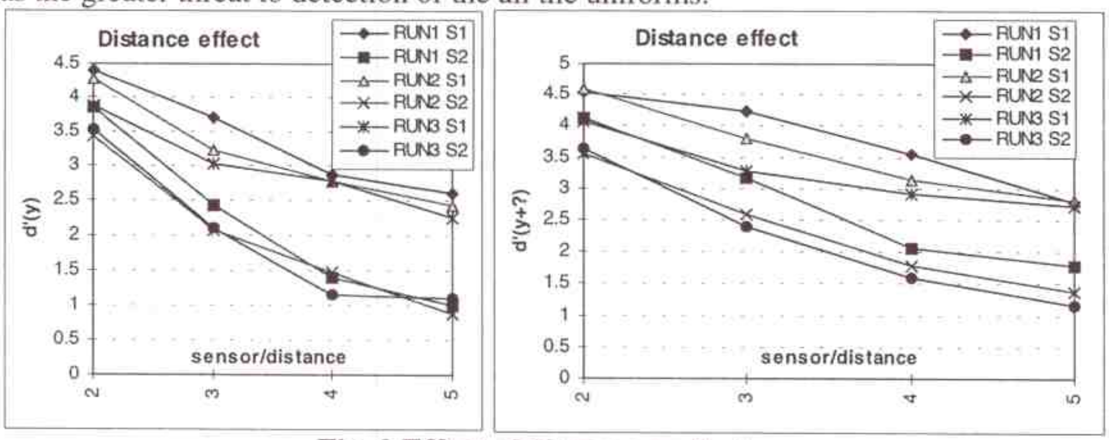
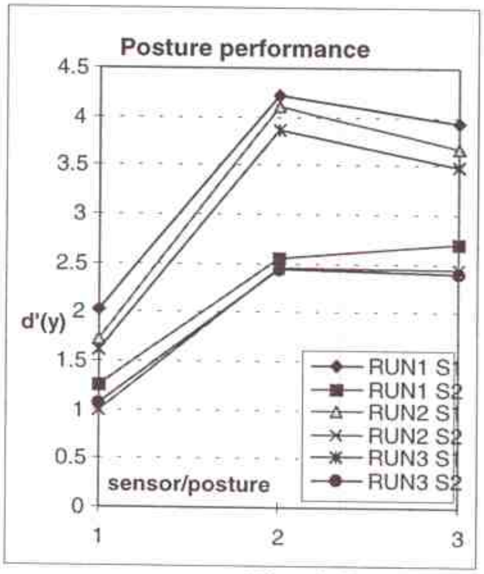


Fig. 2 Effect of distance on dprime

Fig. 3 below shows that the higher the soldier was relative to the ground, the greater was his chance of being detected. Again, this result agrees with common sense and is not surprising.



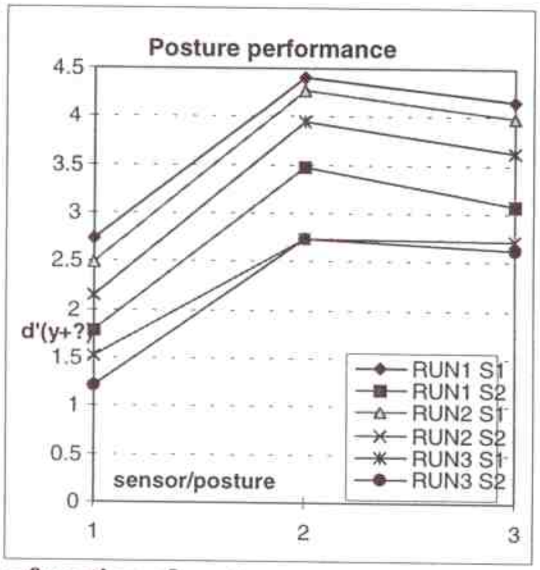


Fig. 3 Dprime as a function of posture

Fig. 4 shows how dprime aggregated over all parameters varied as the run number increased. It is quite surprising, actually how little the performance degraded. Fig. 5 plots the time to respond versus run number and illustrates the effect of learning.

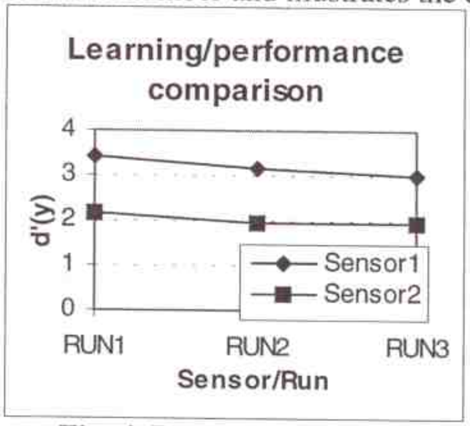


Fig. 4 Dprime versus run

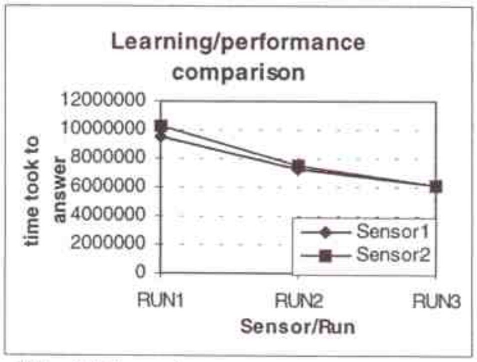


Fig.5 Time to answer versus run

Aside: d' is a standard pyschophysical measure of perceptibility. It is computed from raw test data as the mean z-score for correct detections minus the z-score of false alarms, normalized to the standard deviation in the z-score. It is a measure of the visual signal normalized to the visual noise, i.e., it is the number of standard deviations from the mean

d' is easily related to our sense of the ease or difficulty of detection
d' = 0 => not detectable
d' = 1 => hard to detect
d' = 2 => variable detection response among subjects or at different times
d' = 3 => easy to detect
d' = 4 => pop-out target detected instantly

Computationally for this experiment, we used the following from equations (1) below

$$
\begin{aligned}
&P_d = 1 - \Phi(k - d') \\
&P_{fa} = 1 - \Phi(k) \\
&\textit{where,} \\
&\quad \Phi \text{ is the left tail of the normal distribution} \\
&\quad \text{d' is the target detectability} \\
&\quad \text{k is the particular criterion .}
\end{aligned}
\tag{1}
$$

The dprime of each uniform as seen through the two threat sensors is plotted against each other to see which uniform performed the best under all circumstances and is shown below in Fig. 6. System 8 is the hardest to detect, and system 1 is the easiest to detect for both sensors. Hence, system 8 is the system to wear if you want to avoid detection in the field.

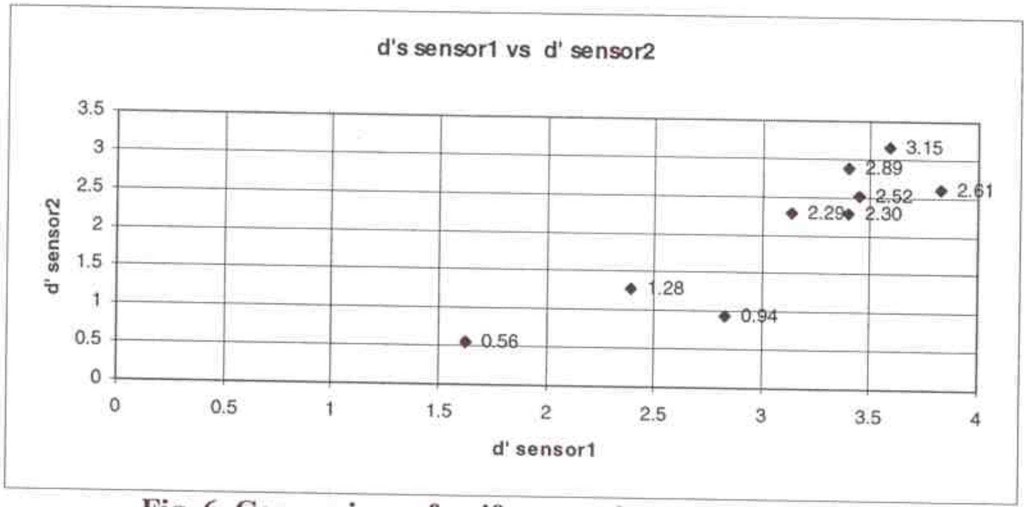


Fig. 6 Comparison of uniform performance by sensor

The graph in Fig. 7 indicates that system 8, 12 and 13 took the longest time to detect, which coincides perfectly with the observation from previous plots that system 8 was the hardest to detect. As time progressed, and the experiment proceeded to run 2 and run 3. This decreased reaction time can be explained by learning on the part of soldiers.

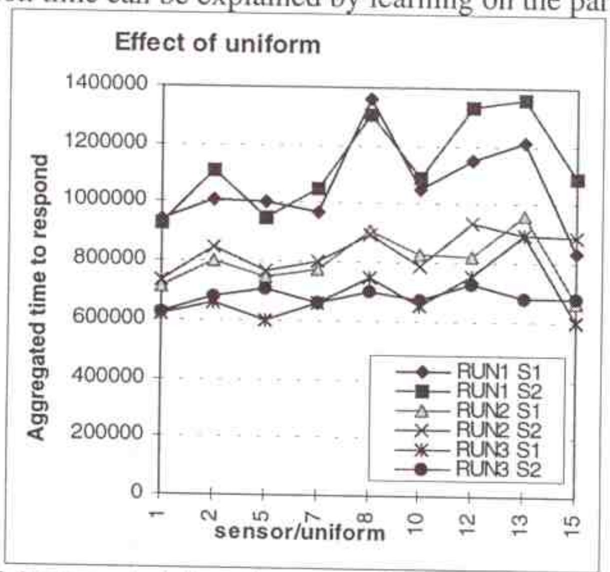


Fig. 7 Aggregated time to respond versus uniform type

The relative importance of the factors considered in the experiment was determined by the ANOVA. Distance, posture, sensor type, uniform, and uniform crossed with sensor were equally important and the most important factors. In decreasing order of importance were the following, uniform crossed with distance, sensor crossed with posture, posture crossed with distance, uniform crossed with posture, sensor crossed with distance, and lastly run number. The fact that run number is the lest significant factor is reassuring since there was some concern about the attention degradation of the subjects. Finally, the statistical model explains ***80%*** of the variance in the data.

Table II
Analysis of Variance

Source	P
DISTANCE	0.000000
POSTURE	0.000000
RUN	0.005394
SENSOR	0.000000
UNIFORM	0.000000
POSTURE*DISTANCE	0.000614
SENSOR*UNIFORM	0.000000
POSTURE*UNIFORM	0.000214
DISTANCE*SENSOR	0.002407
SENSOR*POSTURE	0.000325
UNIFORM*DISTANCE	0.000043

Note: The P-value is the probability that the test statistic will take on a value that is at least as extreme as the observed value of the statistic when the null hypothesis is true, or, the P-value is the smallest level of significance that would lead to rejection of the null hypothesis, from Montgomery's Design and Analysis of Experiments.

Fuzzy Logic (MultiValued Logic) Approach (FLA) to modeling the data

The theory behind the computation of target detection probabilities in the thermal and visible parts of the electromagnetic spectrum has been discussed in [4,5,6]. The theory of the fuzzy logic approach (FLA) and the application of the FLA to the problem of computing target acquisition probabilities to targets in both static infrared and visual scenes has been described in other papers [7,8,9]. The theory remains the same in this paper. The novel application of the FLA in this research was the inclusion of uniform, distance and posture as fuzzy logic categories. A picture of the FIS used to analyze and model the data from this experiment is shown below in Fig. 11.

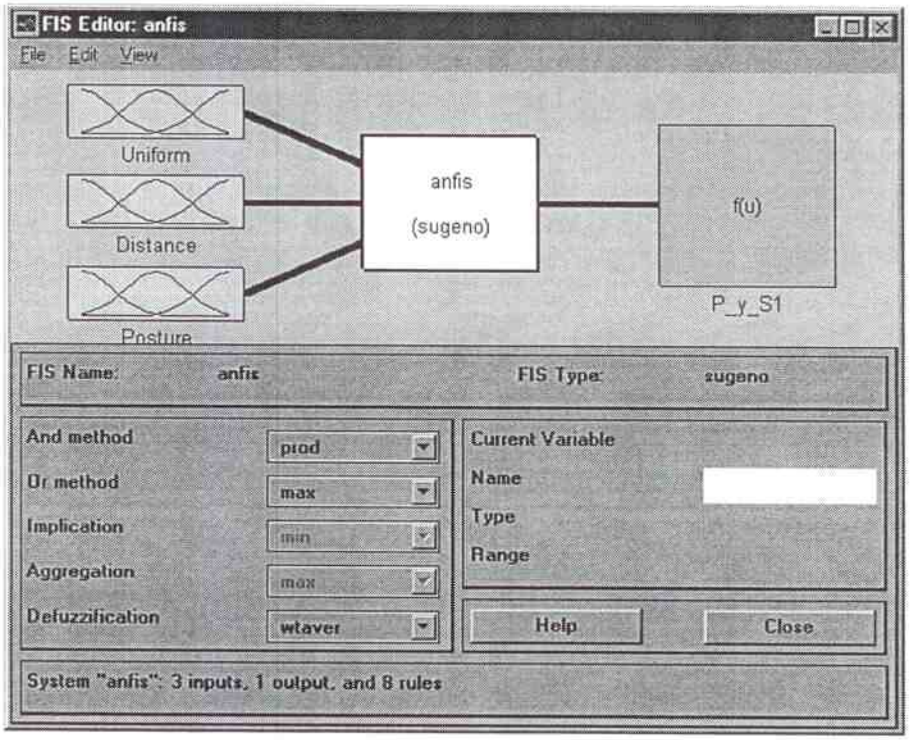


Fig. 8 Fuzzy Inference System (FIS) for used for modeling the data

Fig. 9 through Fig. 12 are graphs of the experimental results versus the FLA predictions. Fig. 9 shows a graph of the FLA predicted Pd and experimental Pd versus image number for one sensor and soldier posture. In this selection of variables the correlation between FLA model and experimental results was 0.84.

Fig. 9 Laboratory data and FLA predictions

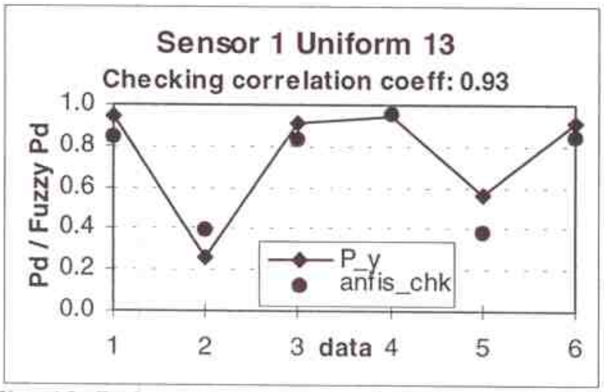


Fig. 10 Laboratory data and FLA predictions

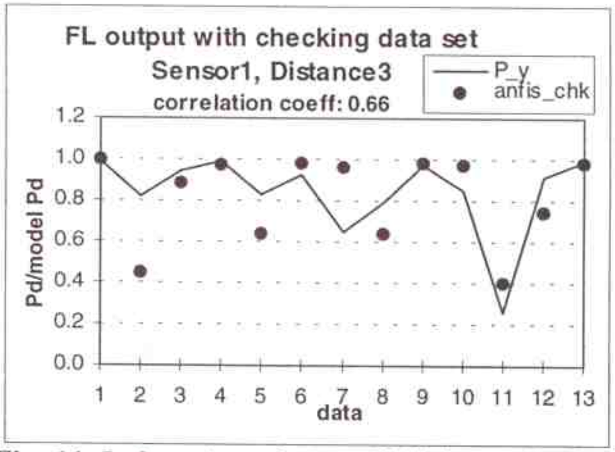
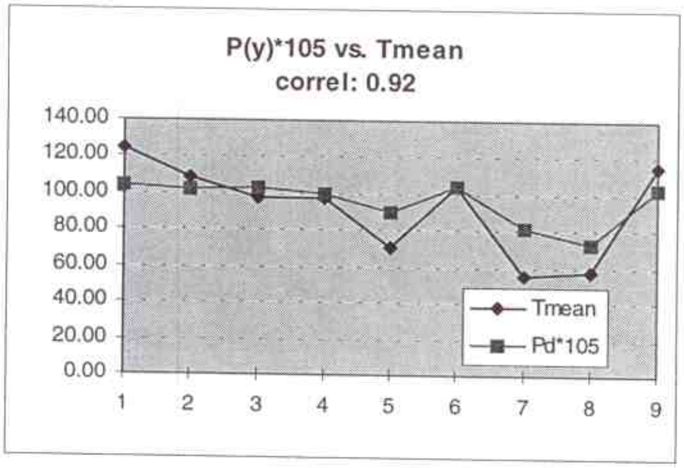


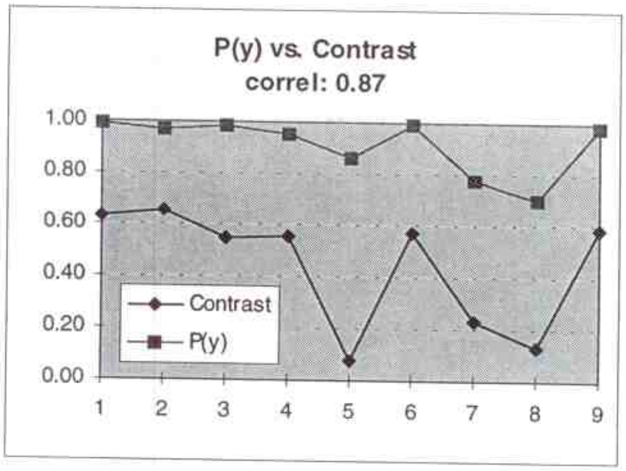
Fig. 11 Laboratory data and FLA predictions

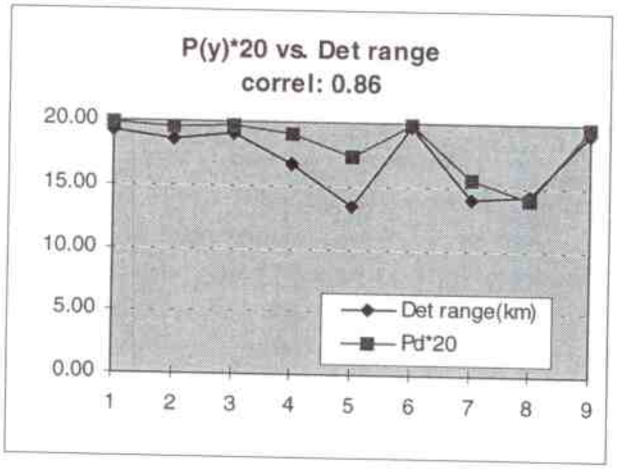
CHAMELEON PLOTS

CAMAELEON [11,12] is a computer model that emulates human early vision and computes the visual detectability of a vehicle in a background. CAMAELEON takes a TIFF image as input and then decomposes it into a set of feature images. The model computes the histogram overlap between user defined target and background regions. The target detection metric is computed from the overlap of histograms for the target and background. CAMAELEON is one of the computational early vision models the U.S. Army is evaluating for the purpose of determining the visibility of ground vehicles under various conditions and was used in this study to compare against laboratory data and fuzzy logic approach (FLA) predictions.

The figures below show graphs of the CAMAELEON predictions and the perception laboratory results.






P(y)*20 vs. Det range
correl: 0.86
20.00
15.00
10.00
5.00
0.00
1
2
3
4
5
6
7
8
9
Det range(km)
Pd*20

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APPENDIX 1

>MODEL DPRIME = CONSTANT +
DISTANCE+POSTURE+SENSOR+UNIFORM+POSTURE*,
>DISTANCE+SENSOR*UNIFORM+POSTURE*UNIFORM+DISTANCE*SENSOR+
UNIFORM*DISTANCE+SENSOR*POSTURE + RUN

Effects coding used for categorical variables in model.

Categorical values encountered during processing are:
DISTANCE (4 levels)
    1,   2,   3,   4
POSTURE (3 levels)
    1,   2,   3
SENSOR (2 levels)
    1,   2
UNIFORM (9 levels)
    1,   2,   3,   4,   5,   6,   7,
    8,   9
RUN (3 levels)
    1,   2,   3

Dep Var: DPRIME   N: 648   Multiple R: 0.865319   Squared multiple R: 0.748777

>CATEGORY DISTANCE POSTURE RUN SENSOR UNIFORM / EFFECT

>MODEL DPRIME = CONSTANT +
DISTANCE+POSTURE+RUN+SENSOR+UNIFORM+POSTURE*,
>DISTANCE+SENSOR*DISTANCE+UNIFORM*DISTANCE+SENSOR*POSTURE+
UNIFORM*POSTURE+,
>UNIFORM*SENSOR

>ESTIMATE

Effects coding used for categorical variables in model.

Categorical values encountered during processing are:
DISTANCE (4 levels)
    2,   3,   4,   5
POSTURE (3 levels)
    1,   2,   3
RUN (3 levels)
    1,   2,   3
SENSOR (2 levels)
    1,   2

UNIFORM (9 levels)

1, 2, 5, 7, 8, 10, 12,
13, 15

3 case(s) deleted due to missing data.

Dep Var: DPRIME N: 645 Multiple R: 0.874878 Squared multiple R: 0.765412

Analysis of Variance

Source	Sum-of-Squares	df	Mean-Square	F-ratio	P
DISTANCE	472.186216	3	157.395405	157.734389	0.000000
POSTURE	406.316684	2	203.158342	203.595885	0.000000
RUN	10.518840	2	5.259420	5.270747	0.005394
SENSOR	227.155656	1	227.155656	227.644883	0.000000
UNIFORM	515.055941	8	64.381993	64.520653	0.000000
POSTURE*DISTANCE	23.978233	6	3.996372	4.004979	0.000614
SENSOR*DISTANCE	14.540569	3	4.846856	4.857295	0.002407
UNIFORM*DISTANCE	63.198347	24	2.633264	2.638936	0.000043
SENSOR*POSTURE	16.254202	2	8.127101	8.144604	0.000325
UNIFORM*POSTURE	44.822475	16	2.801405	2.807438	0.000214
UNIFORM*SENSOR	46.604377	8	5.825547	5.838094	0.000000
Error	567.777174	569	0.997851		

Durbin-Watson D Statistic 2.012
First Order Autocorrelation -0.006